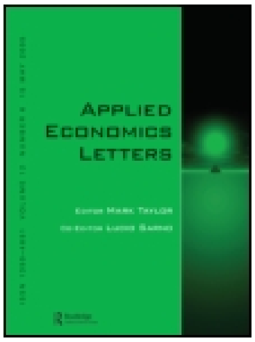

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Can LCCs' economic efficiency create negative externalities for air transport? An analysis of passenger waiting time

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Some features of the low-cost carrier (LCC) management model, such as quick turnaround times, the use of uncrowded airports and expediting check-in processes should have a favourable knock-on effect on their passengers' waiting times at the airport. This article seeks to quantify these possible savings in the low-cost model compared to traditional companies using a database of 37 226 passengers and methodology based on statistical causal inference and the generalized ordered logit model. The results show that LCC passengers are less likely to experience delays of 2 hours or less, although the likelihood that they will have to endure long delays of over 3 hours increases by almost 7.5%. Compared to the greater efficiency of LCCs in the daily movement of passengers averting the most common delays of up to 2 hours, the intensive use of their airplanes results in their lesser ability to respond to unforeseen eventualities with no on-the-spot solution. The little cover that LCCs provide for delays is a strong incentive for their passengers to take out or extend their travel insurance, while airport F&B concessions can benefit from these longer waiting times.

Keywords: low-cost carriers; generalized ordered logit; passenger waiting time; travel insurance

JEL Classification: L90; L93; C25

I. Introduction

A core part of the low-cost airline product is the quick and efficient 25 min turnaround times (Barrett, 2004) that also benefit from the use of secondary and uncrowded airports and, in certain low-cost carriers (LCCs), by the aircraft being cleaned between flights by the cabin crew (Kangis and O´Reilly, 2003). Although there are studies showing that the type of airline does not contribute to a difference in productivity (Assaf, 2011), these quick turnarounds enable more journeys to be made per day per plane, resulting in better fleet utilization and staff productivity (Barrett, 2004). This greater company efficiency ought to have a favourable effect on one of the main inconveniences that air transport passengers have to contend with, i.e., waiting times at the airport.

The low-cost model also possesses other features that, in theory, should significantly reduce waiting times. For example, LCCs generally only offer point-to-point journeys, which prevents delays by interlining, no seat allocation and they do not record frequent-flyer points; low-cost passengers usually arrive at the airport with their boarding

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passes already printed out and, for the most part, do not check their baggage.

Therefore, as punctuality is one of the key points of some LCCs' marketing policies, this article seeks to quantify whether their supposed increased efficiency due to quick turnarounds and fast check-in translates into time savings for passengers. If this is the case, this would mean an increase in air transport's competitiveness over other modes of transport, such as the high-speed train, and we would endeavour to deduce the implications of these results for transport economics.

II. Data and Methodology

Our research uses a database of 37 226 passengers who were interviewed in the departure lounges at eight different Spanish airports, specifically those of Almeria, Alicante, Santiago, Seville, Tenerife and Valencia and the major hubs of Madrid and Barcelona. All the surveys were carried out during the summer of 2010 using questionnaires in five or six languages, depending on passengers' characteristics. This meant that almost 44% of the sample were foreign, namely 16 266. The breadth of the survey campaigns enabled a small average sampling error of ±1.54% calculated at the point of greatest indeterminacy for a 95.45% confidence level.

The proposed methodology is framed by statistical causal inference. This methodology allows consistent estimators of the effects of the evaluated measure to be obtained by determining and isolating the possible impact of additional contaminating variables.

Following Heckman and Vytlacil (2005), we noted whether the observations corresponded to a passenger using an LCC ($D_i = 1$) or some other type of airline ($D_i = 0$). We then estimated the *propensity score* using the binary response model (logit or probit) that maximized the log pseudo-likelihood. The *propensity score* is defined as the conditional probability of 'participating in the evaluated measure', given a vector X of observed covariates. In our case, X comprised the 29 covariates presented in Table 1.

We then calculated the Average Treatment Effect of the measure being evaluated on the response variable, in our case, the probability that the passenger falls into one of the four categories that measure the time that s/he had been waiting to embark when the interview was carried out. The four category outcomes are: less than an hour; between 1 and 2 hours; between 2 and 3 hours and over 3 hours. We used a generalized ordered logit model to calculate the average effect on the selected sample.

Therefore, according to Hirano and Imbens (2001), the generalized ordered logit probability formula for a passenger i who has had to wait for the length of time specified for category j for four category outcomes and frequency weights is

$$\Pr(y_i > j) = \frac{e^{(x_i'\tau_j)}}{1 + e^{(x_i'\tau_j)}}, \quad j = 1, 2, 3$$

where

$$x_i'\tau_j = \tau_{j0} + \alpha_j D_i + \tau_{j1}\,\hat{\varepsilon}(x_i) + \tau_{j2}\,(\hat{\varepsilon}(x_i) - E[\hat{\varepsilon}(x)])\,D_i + \tau_{j3}\,(\hat{\varepsilon}(x_i))^2 + \tau_{j4}\,((\hat{\varepsilon}(x_i) - E[\hat{\varepsilon}(x)])\,D_i)^2 + u_{ij}$$

As in all other discrete choice models, only the sign of the coefficient can be directly interpreted in generalized ordered logit models. So, to obtain more information for analysis, we have used the marginal effects that provide us with a value for the average treatment effect that can be interpreted easily.

III. Results

Table 1 summarizes the results of propensity score estimation in the context of the 29 covariates. We decided on a logit specification, since it maximizes the log pseudo-likelihood (–22143095) when compared to a probit (–22154311). The significance of each of the individual covariates is of no importance for our analysis. As explained above, the purpose of the propensity score is simply to make the individuals from the treatment group (LCC passengers) and the control group (other airline type passengers) as homogeneous as possible, as far as the 29 covariates are concerned.

Finally, Table 2 gives the marginal effect at the mean of the generalized ordered logit estimation that measures the increase (Δ) or decrease (∇) in the likelihood that the LCC passenger has had to endure each of the four possible waiting time categories compared to passengers on other airlines.

IV. Conclusions

Unlike what might be anticipated *a priori*, the results show that LCCs' short 'on the ground' turnaround times and their supposed fast check-in and embarkation process times have not had a positive effect on passengers' enforced waiting times at the terminals. In fact, the empirical evidence shows that LCC passengers are more likely to be exposed to waiting times at the terminal that exceed 3 hours, with an increase of almost 7.5%, to be specific. This greater exposure to long waiting times is counterbalanced by a lesser likelihood of shorter delays, especially delays of 1–2 hours.

Table 1. Propensity score

Covariates		Explanation	Coefficient
Sex		1 if male, 0 if female.	0.097(0.040)**
Age		1 < 30; 2 = 31–49; 3 = 50–64; 4 > 65.	−0.274(0.033)***
Spanish		1 if passenger is Spanish, 0 if passenger is foreign.	0.043(0.033)
Education		1 = no formal or only primary education; 2 = completed secondary education; and 3 = holds university degree.	−0.026(0.034)
Reason	Business	1 if trip is for business reasons, 0, otherwise.	−0.645(0.065)***
Base category: Vacation passenger	Visiting friends and relatives	1 if trip is for visiting friends and relatives, 0, otherwise.	0.035(0.053)
Employment status	Housewife	1 if passenger is a housewife, 0, otherwise.	−0.252(0.138)*
Base category:	Student	1 if passenger is a student, 0, otherwise.	0.117(0.073)
Employee	Retired	1 if passenger is retired, 0, otherwise.	−0.113(0.086)
	Self-employed	1 if passenger is freelance or self-employed, 0, otherwise.	−0.044(0.057)
	Unemployed	1 if passenger is unemployed, 0, otherwise.	−0.021(0.100)
Connecting flight		1 if passenger is connecting to another flight at the airport, 0, if travelling no further.	−1.724(0.096)***
Destination	Eurozone destination	1 if passenger is taking an international flight with a final destination in a Eurozone country, 0, otherwise.	0.958(0.048)***
Base category: Domestic flight	Non-Eurozone destination	1 if passenger is taking an international flight with a final destination outside the Eurozone, 0, otherwise.	−0.980(0.106)***
Duration of trip		1 = 0–1 days; 2 = 2–7 days; 3 = 8–14; 4 = 15–30; 5 > 30 days.	−0.242(0.024)***
Accessibility	Taxi	1 if passenger has travelled to the airport by taxi, 0, otherwise.	0.055(0.056)
Base category:	Courtesy bus	1 if passenger has travelled to the airport by courtesy bus, 0, otherwise.	−0.954(0.097)***
Private vehicle	Rent-a-car	1 if passenger has travelled to the airport by rental car, 0, otherwise.	0.535(0.096)***
	Public transport	1 if passenger has travelled to the airport by public transport, 0, otherwise.	0.581(0.054)***
Hotel		1 if passenger has stayed in hotels or similar, 0, otherwise	0.184(0.061)***
Group size		1 = travelling alone; 2 = 2 people; 3 = 3 or more people.	−0.062(0.072)
Children		1 if passenger is flying with children, 0, otherwise.	−0.245(0.095)**
Accompaniment	Work	1 if passenger is travelling with work colleagues, 0, otherwise.	−0.165(0.136)
	Friends	1 if passenger is travelling with friends, 0, otherwise.	0.015(0.128)
	Family	1 if passenger is travelling with family, 0, otherwise.	−0.052(0.097)
Farewell		1 if someone goes to see the passenger off at the airport, 0, otherwise.	0.464(0.055)***
Autonomous community		1 if passenger's place of residence is in the region where the airport is located, 0, otherwise.	0.354(0.051)***
Airport traffic		Thousands of passengers per week at each airport at the time that the surveys were taken.	−0.005(0.000)***
Hub		1 if the airport is Madrid–Barajas or Barcelona, 0, otherwise	0.176(0.164)**

Notes: SEs, in brackets, robust to heteroscedasticity. One, two and three asterisks indicate coefficient significance at the 10%, 5% and 1% levels, respectively.

Table 2. Marginal effect of the generalized ordered logit estimation

	< 1 hour	1–2 hours	2–3 hours	>3 hours
LCC (Di)	∇1.08(0.28)***	∇4.51(0.10)***	∇1.87(1.17)	Δ 7.47(1.25)***
$\hat{\varepsilon}(x_i)$	Δ15.15(2.20)***	Δ111.24(7.00)***	Δ3.84(7.53)	∇130.23(7.36)***
$(\hat{\varepsilon}(x_i))^2$	∇17.28(2.94)***	∇100.28(9.29)***	Δ6.77(10.29)	Δ110.79(10.23)***
$(\hat{\varepsilon}(x_i) - E[\hat{\varepsilon}(x)])D_i$	Δ0.28(1.24)	∇12.23(3.90)***	Δ1.42(4.44)	Δ10.52(4.55)**
$((\hat{\varepsilon}(x_i) - E[\hat{\varepsilon}(x)])D_i)^2$	Δ19.72(4.40)***	Δ108.00(14.09)***	Δ10.63(16.16)	∇138.36(16.48)***

Notes: SEs, in brackets, robust to heteroscedasticity. Two and three asterisks indicate coefficient significance at the 5% and 1% levels, respectively.

This finding is hard to imagine, *a priori*, and must be put down, primarily, to LCCs' greater efficiency, punctuality and speed of check-in having a positive effect on the passenger by preventing the usual waits of up to 2 hours, but their ability to respond is less agile when some unforeseen eventuality occurs, and this results in a greater likelihood that passengers will have to endure a waiting time that exceeds 3 hours. In other words, the intensive use that is made of the aircraft means that whenever one of them suffers a mishap that cannot be put right quickly, this causes an enormous delay as there are no other aircraft available to take its place. This would therefore be an unwanted side effect of LCCs' better fleet utilization.

This finding is even more important when we take into account that LCCs do not usually offer generous compensation packages in the form of accommodation, meals or alternative transport for passengers who endure long delays (eventualities that, according to Castillo-Manzano and Marchena-Gómez (2010), are better catered for by network carriers). This finding is therefore a clear incentive for passengers to take out ample travel insurance which would provide them with compensation, given the greater likelihood of being subject to a long delay, either the policies sold by the LCCs themselves with their tickets, or those linked to premium credit cards (gold, platinum or similar). This would compensate passengers for the surcharge that LCCs impose on the use of these types of cards (distinctly more than for debit cards), as they usually cover the eventuality of long delays in the journey.

In other respects, this finding can also be considered an indirect test of the need for airports to continue to provide a wide range of services to cater for passengers' requirements during the era of the LCCs, especially restaurants and cafeterias (see Castillo-Manzano and López-Valpuesta (2013) on waiting times as the main reason for the consumption of food and drink at airports.), stores and even hotels in the surrounding area.

Moreover, in the case of LCCs, longer access times to the airport from the city and vice versa also have to be added to this likelihood of having to contend with longer waiting times, as the airports that these companies use are often at a significant distance from the main cities. To summarize, the LCCs have managed to reduce the cost of air transport, but they have not necessarily made it easier for the passenger with respect to waiting times. Their product is therefore more oriented towards price-sensitive rather than time-sensitive passengers.

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